How to Create an ARIMA Model for Time Series Forecasting in Python

INTERMEDIATE MACHINE LEARNING PYTHON STRUCTURED DATA SUPERVISED TECHNIQUE TIME SERIES

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Introduction

A popular and widely used statistical method for time series forecasting is the ARIMA model. Exponential smoothing and ARIMA models are the two most widely used approaches to time series forecasting and provide complementary approaches to the problem. While exponential smoothing models are based on a description of the trend and seasonality in the data, ARIMA models aim to describe the autocorrelations in the data.

To know about seasonality please refer to this blog.

Before we talk about the ARIMA model, let's talk about the concept of stationarity and the technique of differencing time series.

Stationarity

A stationary time series data is one whose properties do not depend on the time, That is why time series with trends, or with seasonality, are not stationary. the trend and seasonality will affect the value of the time series at different times, On the other hand for stationarity it does not matter when you observe it, it should look much the same at any point in time. In general, a stationary time series will have no predictable patterns in the long-term.

ARIMA is an acronym that stands for Auto-Regressive Integrated Moving Average. It is a class of model that captures a suite of different standard temporal structures in time series data.

In this tutorial, We will talk about how to develop an ARIMA model for time series forecasting in Python.

An ARIMA model is a class of statistical models for analyzing and forecasting time series data. It is really simplified in terms of using it, Yet this model is really powerful.

ARIMA stands for Auto-Regressive Integrated Moving Average.

The parameters of the ARIMA model are defined as follows:

p: The number of lag observations included in the model, also called the lag order.
d: The number of times that the raw observations are differenced, also called the degree of difference.
q: The size of the moving average window, also called the order of moving average.
A linear regression model is constructed including the specified number and type of terms, and the data is prepared by a degree of differencing in order to make it stationary, i.e. to remove trend and seasonal structures that negatively affect the regression model.

STEPS

1. Visualize the Time Series Data
2. Identify if the date is stationary
3. Plot the Correlation and Auto Correlation Charts
4. Construct the ARIMA Model or Seasonal ARIMA based on the data

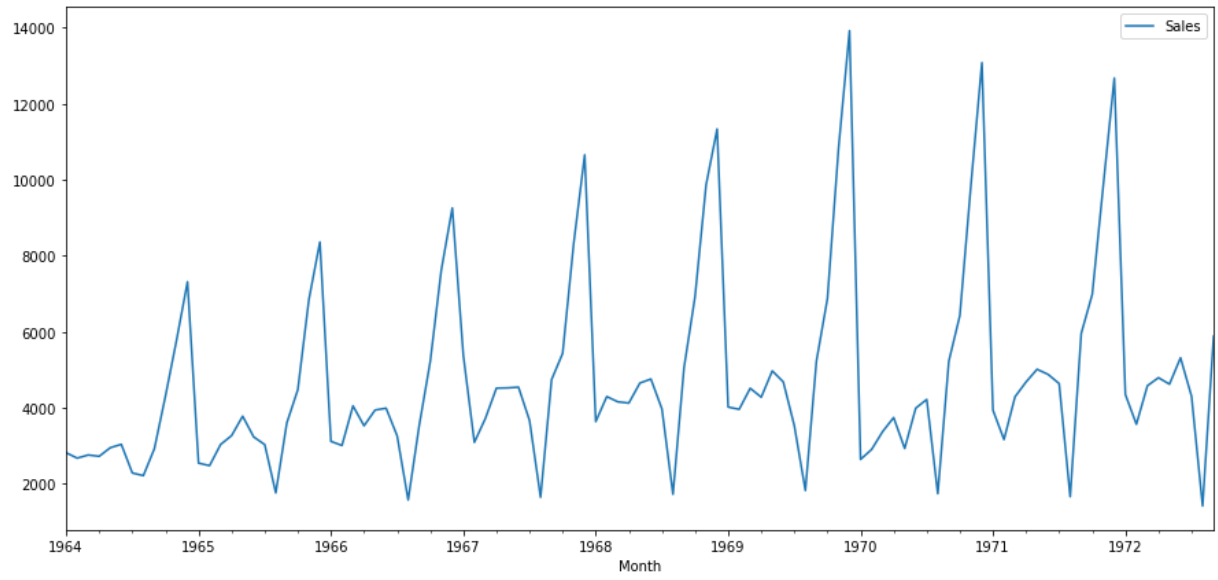
Let's Start

```
import numpy as np import pandas as pd import matplotlib.pyplot as plt %matplotlib inline
```

In this tutorial, I am using the below dataset.

```
df=pd.read_csv('time_series_data.csv') df.head() # Updating the header df.columns=["Month","Sales"] df.head() df.describe() df.set_index('Month',inplace=True) from pylab import rcParams rcParams['figure.figsize'] = 15, 7 df.plot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x28ec41d8940>
```



if we see the above graph then we will able to find a trend that there is a time when sales are high and vice versa. That means we can see data is following seasonality. For ARIMA first thing we do is identify if the data is stationary or non – stationary. if data is non-stationary we will try to make them stationary then we will process further.

Let's check that if the given dataset is stationary or not, For that we use adfuller.

```
from statsmodels.tsa.stattools import adfuller
```

I have imported the adfuller by running the above code.

```
test_result=adfuller(df['Sales'])
```

To identify the nature of data, we will be using the null hypothesis.

H0: **The null hypothesis:** It is a statement about the population that either is believed to be true or is used to put forth an argument unless it can be shown to be incorrect beyond a reasonable doubt.

H1: **The alternative hypothesis:** It is a claim about the population that is contradictory to H_0 and what we conclude when we reject H_0.

#Ho: It is non-stationary
#H1: It is stationary

We will be considering the null hypothesis that data is not stationary and the alternate hypothesis that data is stationary.

```
def adfuller_test(sales): result=adfuller(sales) labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observations'] for value,label in zip(result,labels): print(label+' : '+str(value) ) if result[1] <= 0.05: print("strong evidence against the null hypothesis(Ho), reject the null hypothesis. Data is stationary") else: print("weak evidence against null hypothesis,indicating it is non-stationary ") adfuller_test(df['Sales'])
```

After running the above code we will get P-value,

```
ADF Test Statistic : -1.8335930563276237 p-value : 0.3639157716602447 #Lags Used : 11 Number of Observations : 93
```

Here P-value is 0.36 which is greater than 0.05, which means data is accepting the null hypothesis, which means data is non-stationary.

Let's try to see the first difference and seasonal difference:

```
df['Sales First Difference'] = df['Sales'] - df['Sales'].shift(1) df['Seasonal First Difference']=df['Sales']-df['Sales'].shift(12) df.head()
```

Month	Sales	Sales First Difference	Seasonal First Difference
1964-01-01	2815	NaN	NaN
1964-02-01	2672	-143.0	NaN
1964-03-01	2755	83.0	NaN
1964-04-01	2721	-34.0	NaN
1964-05-01	2946	225.0	NaN

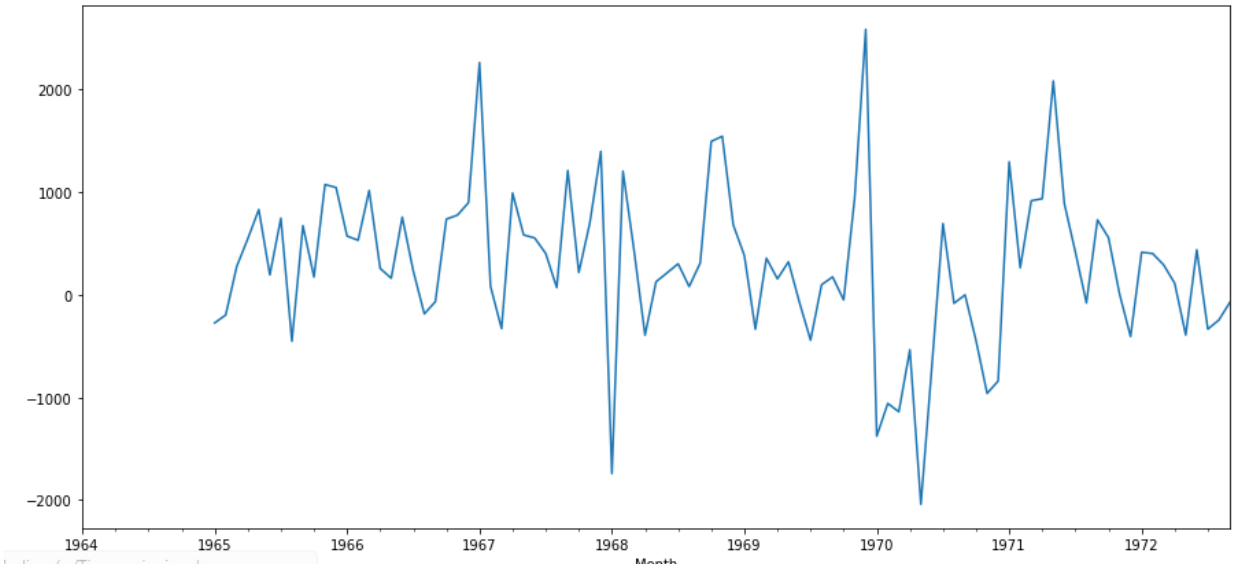
```
# Again testing if data is stationary adfuller_test(df['Seasonal First Difference'].dropna())
```

```
ADF Test Statistic : -7.626619157213163 p-value : 2.060579696813685e-11 #Lags Used : 0 Number of Observations : 92
```

Here P-value is 2.06, which means we will be rejecting the null hypothesis. So data is stationary.

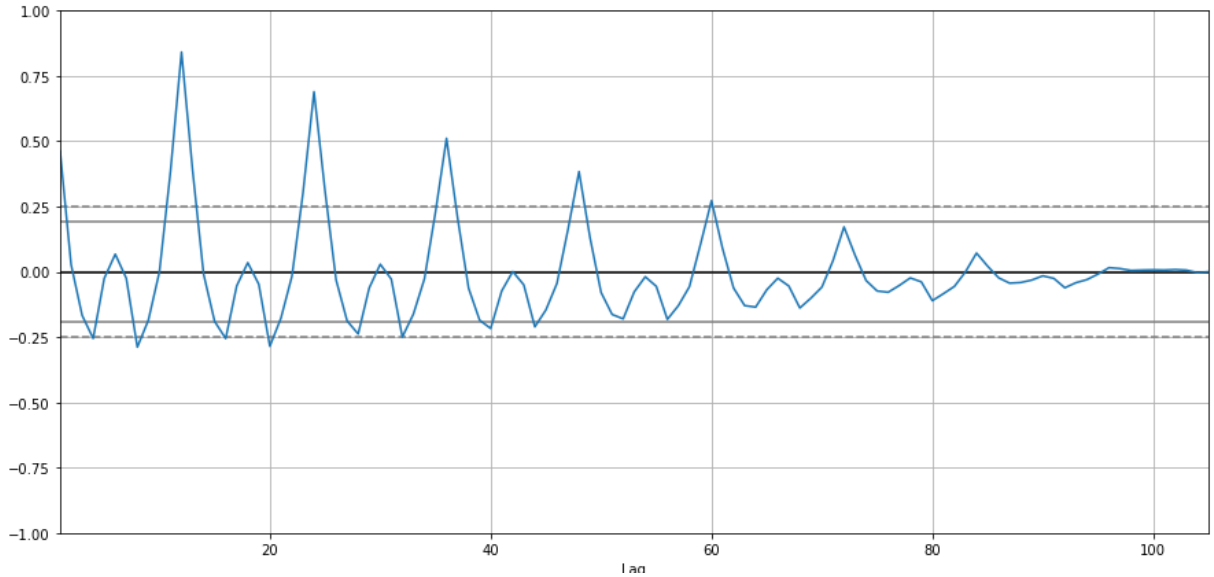
```
df['Seasonal First Difference'].plot()
```

<matplotlib.axes._subplots.AxesSubplot at 0x28ec46f2d30>

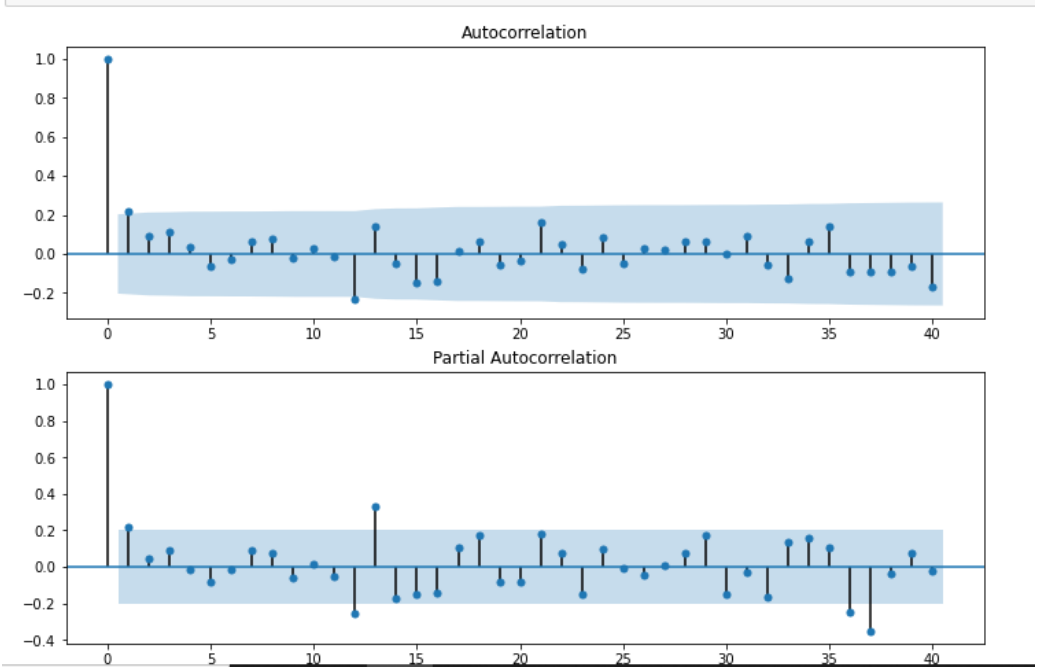


I am going to create auto-correlation :

```
from pandas.plotting import autocorrelation_plot autocorrelation_plot(df['Sales']) plt.show()
```




```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf import statsmodels.api as sm fig = plt.figure(figsize=(12,8)) ax1 = fig.add_subplot(211) fig = sm.graphics.tsa.plot_acf(df['Seasonal First Difference'].dropna(),lags=40,ax=ax1) ax2 = fig.add_subplot(212) fig = sm.graphics.tsa.plot_pacf(df['Seasonal First Difference'].dropna(),lags=40,ax=ax2)
```




```
# For non-seasonal data #p=1, d=1, q=0 or 1 from statsmodels.tsa.arima_model import ARIMA
model=ARIMA(df['Sales'],order=(1,1,1)) model_fit=model.fit() model_fit.summary()
```

ARIMA Model Results

Dep. Variable:	D.Sales	**No. Observations:**	104
Model:	ARIMA(1, 1, 1)	**Log-Likelihood**	-951.126
Method:	css-mle	**S.D. of innovations**	2227.262
Date:	Wed, 28 Oct 2020	**AIC**	1910.251
Time:	11:49:08	**BIC**	1920.829
Sample:	02-01-1964 – 09-01-1972	**HQIC**	1914.536

	coef	std err	z	P>|z|	[0.025	0.975]
const	22.7845	12.405	1.837	0.066	-1.529	47.098
ar.L1.D.Sales	0.4343	0.089	4.866	0.000	0.259	0.609
ma.L1.D.Sales	-1.0000	0.026	-38.503	0.000	-1.051	-0.949

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	2.3023	+0.0000j	2.3023	0.0000
MA.1	1.0000	+0.0000j	1.0000	0.0000

```
df['forecast']=model_fit.predict(start=90,end=103,dynamic=True) df[['Sales','forecast']].plot(figsize=(12,8))
```

```
import statsmodels.api as sm model=sm.tsa.statespace.SARIMAX(df['Sales'],order=(1, 1, 1),seasonal_order=(1,1,1,12)) results=model.fit() df['forecast']=results.predict(start=90,end=103,dynamic=True) df[['Sales','forecast']].plot(figsize=(12,8))
```

```
from pandas.tseries.offsets import DateOffset future_dates=[df.index[-1]+ DateOffset(months=x)for x in range(0,24)] future_datest_df=pd.DataFrame(index=future_dates[1:],columns=df.columns) future_datest_df.tail() future_df=pd.concat([df,future_datest_df]) future_df['forecast'] = results.predict(start = 104, end = 120, dynamic= True) future_df[['Sales', 'forecast']].plot(figsize=(12, 8))
```

Conclusion

Time Series forecasting is really useful when we have to take future decisions or we have to do analysis, we can quickly do that using ARIMA, there are lots of other Models from we can do the time series forecasting but ARIMA is really easy to understand.

I hope this article will help you and save a good amount of time. Let me know if you have any suggestions.

HAPPY CODING.

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Article Url - https://www.analyticsvidhya.com/blog/2020/10/how-to-create-an-arima-model-for-time-series-forecasting-in-python/

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